

# Gaussian Process based Radio Map Recovery

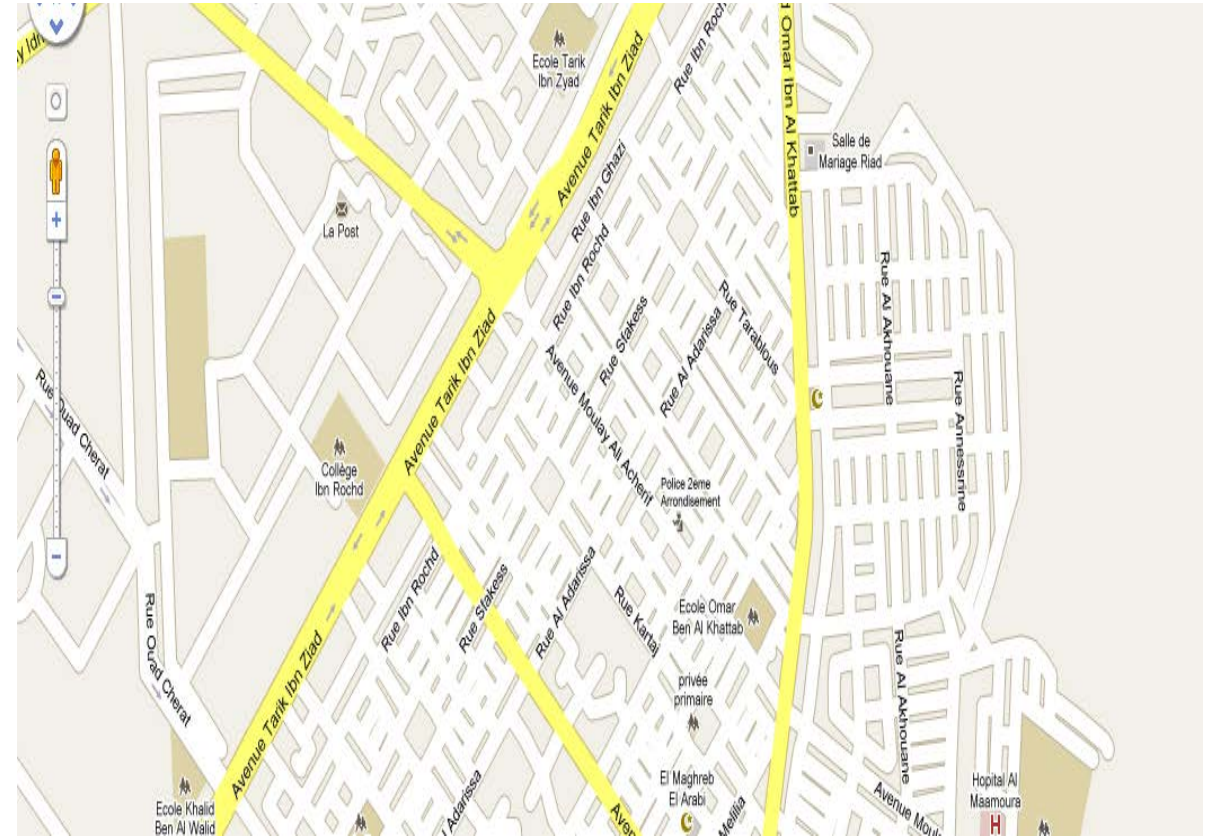
HuangZili

# Content

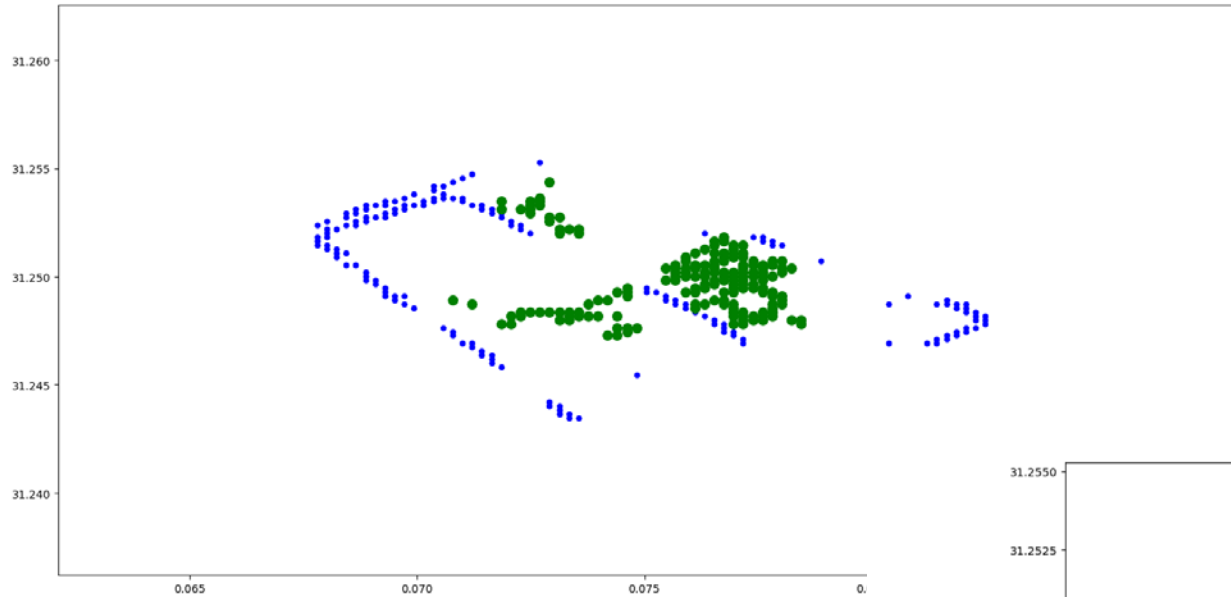
- + 1. Research Background
- + 2. Method
- + 3. System

# Background

- To model the signal strength in one area, we can collect data from the users' mobile devices.
- The users are not uniformly distributed on the map. Some places like small streets may not be covered.
- How can we solve this problem?
- To predict the signal strength on the small roads based on signal strength on the main roads

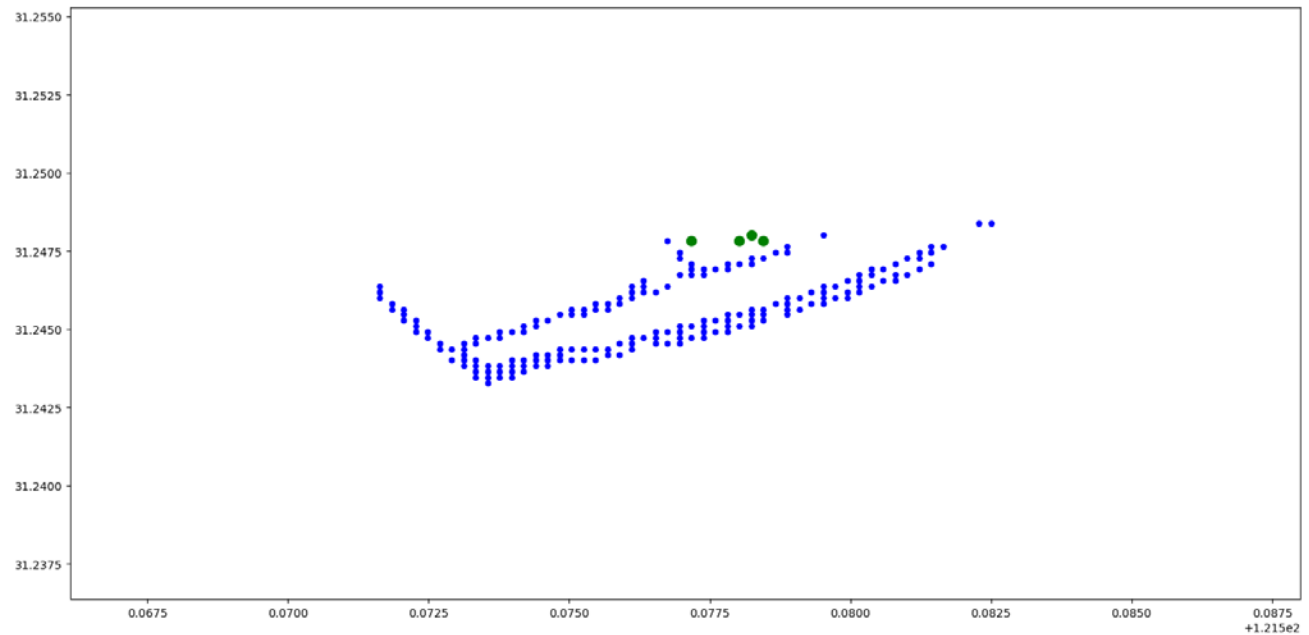


# Background



Blue dots:  
training samples  
Green dots:  
test samples

The test set is not generated by randomly sampling in the feature space.



# Method

## Gaussian Process Regression

### joint distribution

$$\begin{bmatrix} \mathbf{y} \\ f(\mathbf{x}_*) \end{bmatrix} \sim \mathcal{N} \left( \mathbf{0}, \begin{bmatrix} \mathbf{K}(\mathbf{X}, \mathbf{X}) + \sigma_n^2 \mathbf{I} & \mathbf{k}(\mathbf{X}, \mathbf{x}_*) \\ \mathbf{k}(\mathbf{x}_*, \mathbf{X}) & k(\mathbf{x}_*, \mathbf{x}_*) \end{bmatrix} \right)$$

### marginal distribution

$$f(\mathbf{x}_*) = \mathbf{k}_*^T (\mathbf{K} + \sigma_n^2 \mathbf{I})^{-1} \mathbf{y} = \mathbf{k}_*^T \boldsymbol{\alpha},$$

$$V(\mathbf{x}_*) = k(\mathbf{x}_*, \mathbf{x}_*) - \mathbf{k}_*^T (\mathbf{K} + \sigma_n^2 \mathbf{I})^{-1} \mathbf{k}_*,$$

# Method

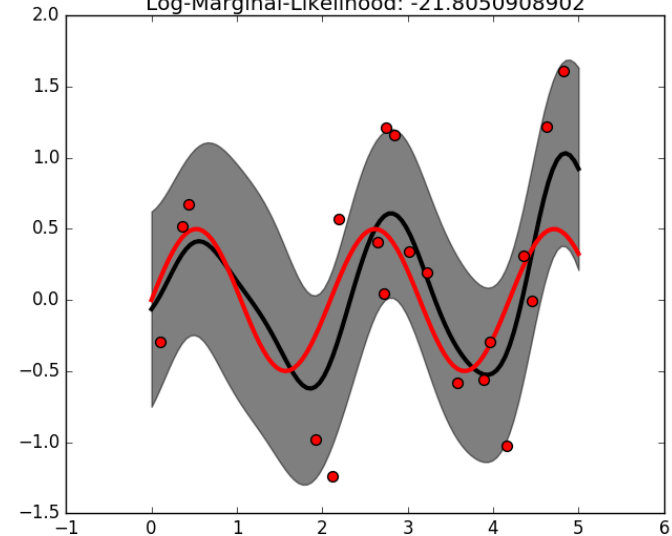
## Advantage of GPR

- (1) nonparametric
- (2) The prediction is probabilistic

## Disadvantage of GPR

- (1) Gaussian processes are not sparse
- (2) They lose efficiency in high dimensional spaces

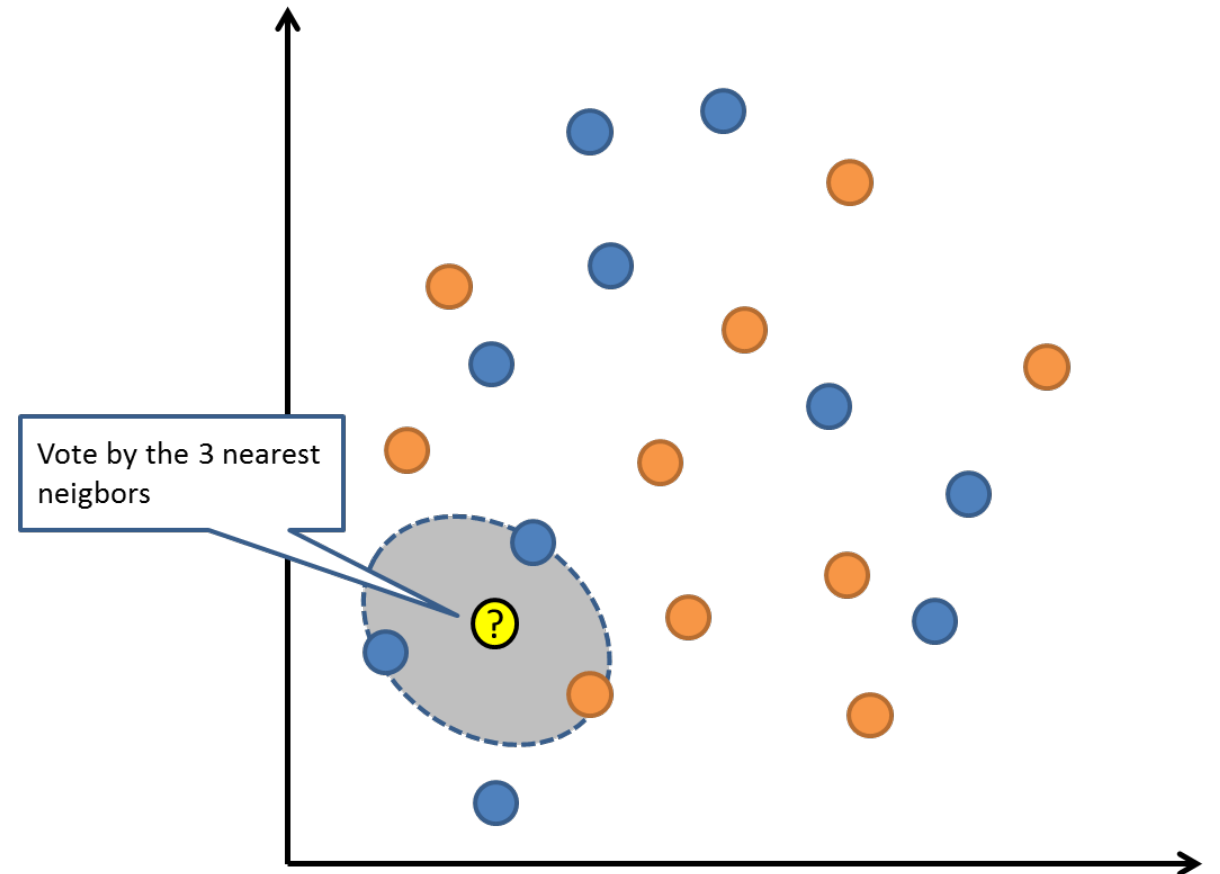
Initial:  $1 \times 2 \times \text{RBF}(\text{length\_scale}=1) + \text{WhiteKernel}(\text{noise\_level}=1e-05)$   
Optimum:  $0.64 \times 2 \times \text{RBF}(\text{length\_scale}=0.365) + \text{WhiteKernel}(\text{noise\_level}=0.294)$   
Log-Marginal-Likelihood: -21.8050908902



# Method

## K-nearest neighbors

- 1.distance measure
- 2.combination methods



# Method

## + KNN-GPR

### + Assumption

The signal strength follows Gaussian distribution in a local area.

### + Process

- 1. Preprocess the data
- 2. Find k-nearest neighbors of the test sample
- 3. Apply Gaussian process regression in the k-nearest neighbors



# Performance on our dataset

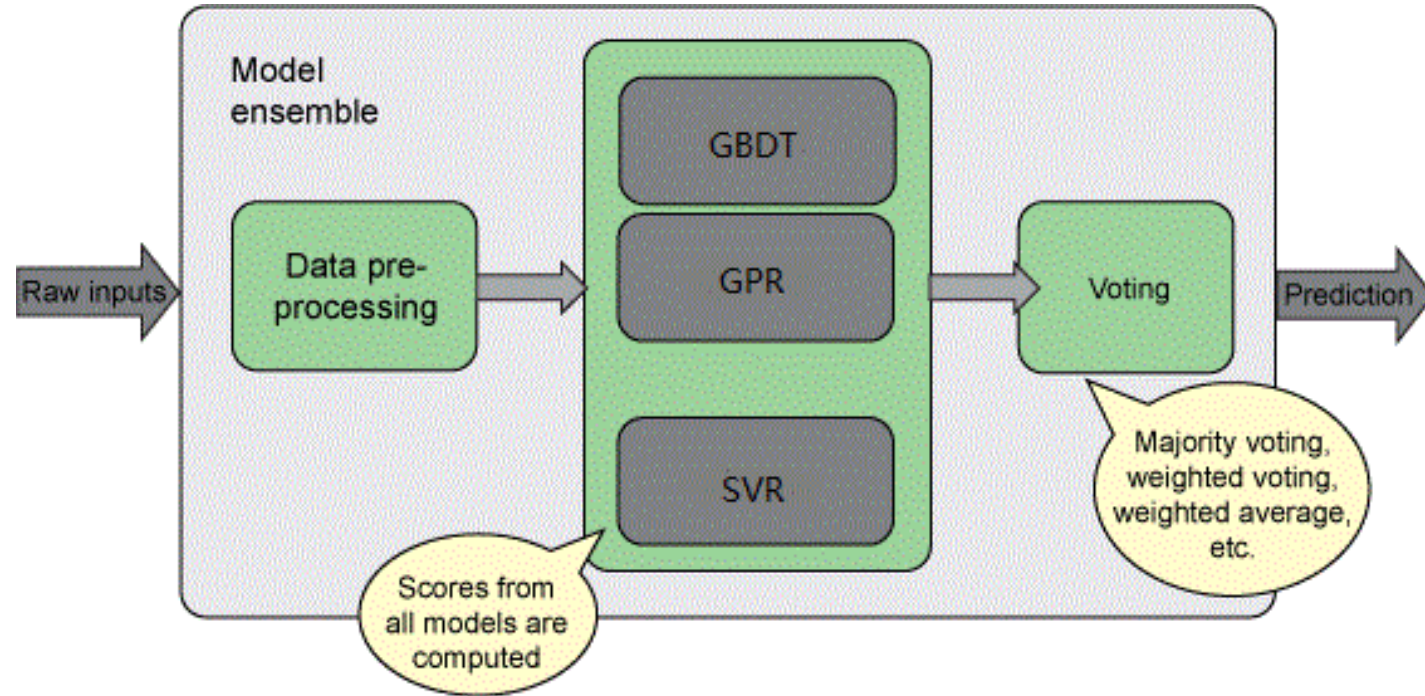
Methods	KNN(k=5)	KNN(k=10)	KNN(k=15)	KNN(k=30)	GP	KNN-GP
MAE	6.56	6.78	6.91	7.45	6.28	5.87

comparison of different methods

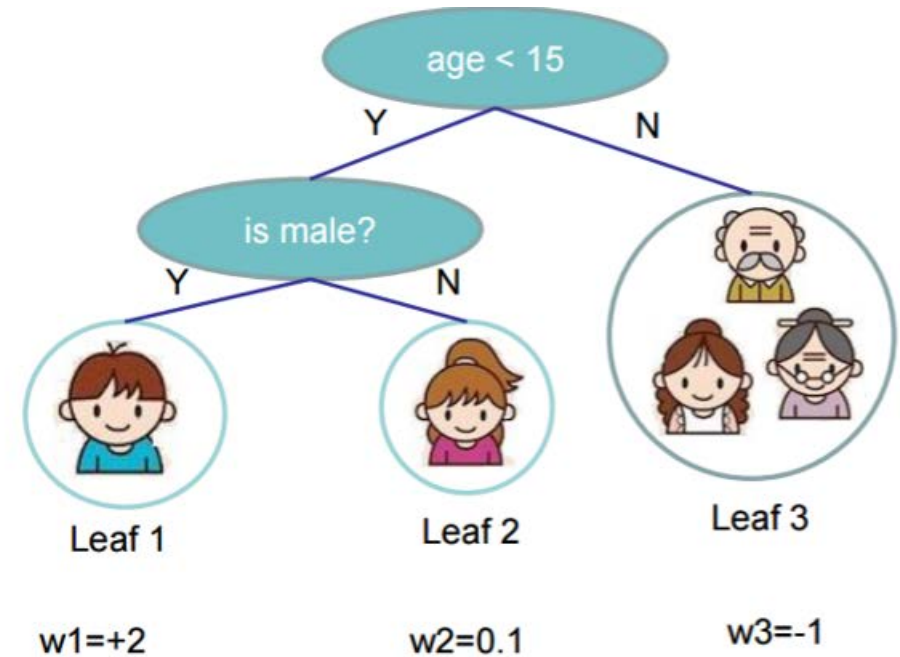
kernel	RBF	Matern(nu=0.5)	Matern(nu=1.5)	Matern(nu=2.5)	RationalQuad ratic
MAE	5.87	6.98	6.15	6.04	7.84

comparison of different kernels

# Method



GBDT: Gradient Boosted Decision Trees



# Method

Methods	Gaussian Process Regression	Gradient Boosted Decision Trees	Support Vector Regression	Model ensemble(linear regression)	Model ensemble(average)
MAE	8.20	8.38	10.51	8.88	8.02

# System

- + A Gaussian Process Positioning System

$$\hat{t} = \arg \max_t \prod_{j:s_j \neq \{\}} p_j(s_j | t)$$

- +  $p_j(s_j | t)$  the likelihood of receiving a signal strength  $s_j$  from the j-th base station on position t.
- +  $p_j(s_j | t)$  is given by the Gaussian process regression

# System

scale(m)	50	100	150	200
accuracy	0.3	0.525	0.375	0.65

results of position prediction with  
no less than 3 data records

number of records	$\geq 3$	$\geq 4$	$\geq 5$	$\geq 6$
accuracy	0.525	0.655	0.75	1

results of position prediction  
with different number of data  
records



**THANKS**